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PREDICTION OF PLASMA ARC CUTTING PERFORMANCE FOR SS-304 MATERIAL USING ARTIFICIAL NEURAL NETWORK

A. H. PATEL[1] & Dr A. B. PANDEY[2]

[1]Lecturer, Department of Mechanical Engineering, Polytechnic, The Maharaja Sayajirao University of Baroda Vadodara, Gujarat, India

[2]Assistant Professor, Department of Mechanical Engineering, Faculty of Technology & Engineering, The Maharaja Sayajirao University of Baroda, Vadodara, Gujarat, India

ABSTRACT

A number of cutting parameters are responsible for the quality of cut in plasma arc cutting (PAC) process, so the prediction of process performance is important to set the control parameters for achieving the adequate cut quality. This paper attempts to develop predictive models for Current input parameters, stand-off distance, pressure and cutting speed and their effects on output responses like material remove rate (MRR), top kerf width, bottom kerf width, straightness, and bevel angle during PAC. All the experiments were carried out on 6 mm thick SS-304 material, different output responses were measured and various artificial neural network (ANN) architecture models were developed in Easy NN software for prediction and were determined by calculating various errors and variances between actual experiments. The limiting value for all the errors over the entire data is selected as 5% and the maximum number of training cycles are limited to 1000000 for each learning set. In the present work, it is found that 4-6-5 ANN architecture is the best model structure for selected input parameters.

KEYWORDS: Plasma Arc Cutting Process, Artificial Neural Networks & Modeling

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Abbreviations

- PAC Plasma arc cutting
- MRR Material removal rate
- ANN Artificial neural network
- SOD standoff distance
- MRR material remove rate
- KT Top kerf width
- KB Bottom kerf width
- ST straightness
- θ bevel angle
- L9 Orthogonal array of 9 runs
- L18 Orthogonal array of 18 runs

INTRODUCTION

Nowadays several non-traditional cutting processes are available, from which Plasma arc cutting (PAC) is a non-traditional thermal cutting process used for making various parts in modern manufacturing industries like a shipyard, chemical, nuclear, automotive, fabrication and pressure vessel, etc. It is capable of cutting various electrically conductive materials. Its serving action is produced by melting a specific area with the heat of a constricted arc, then removing the molten material with a high-velocity jet of hot ionized gas expelled from the nozzle orifice of the cutting torch [1]. No. of researchers have studied the plasma arc cutting process in many points of view but in this paper, the use of artificial neural network in plasma arc cutting process was considered. Radovanovic M. et al. developed ANN to predict the ten point height of irregularities (Rz) in PAC process, for that purpose three layered feed forward back propagations architecture was used in terms of three input parameters, current, plate thickness, cutting speed and was found that ANN model with 3-3-1 architecture gives minimal surface roughness value [2]. Wang j. et al. conducted a study on neural network modeling with the help of back propagations learning algorithm and trained the data for cutting surface quality of plasma arc cutting like cut shape neuro-predictor, dross attached level, and the cut surface roughness neuro-estimators and estimated results for the effectiveness and accepted the estimated accuracy for the selected model [3]. Mohd Idris Shah Ismail et al. predicted the hardness distribution in plasma arc surface hardening process with the help of back propagation method and Leven berg-Marquardt algorithm, trained the neural network models and compared them with statistical regression models and found that hardness distribution was accurate as per prediction [4]. J. Y. Wang et al. developed neural network models for carbon steel material to predict the cut shape and estimated cutting conditions in PAC [5]. John Kechagias et al. conducted an experiment on St37 mild steel plate with the help of CNC plasma arc cutting machine, they used L18 orthogonal array in which seven factors were selected and measured the output response of bevel angle, after that by using experimental data with feed forward back propagation algorithm in ANN model and predicted results which were accurate and further ANN model was used for the optimization of CNC plasma-arc cutting parameters [6].

EXPERIMENTAL PARAMETERS

However, prediction of their effect on output parameters must be established to precisely control the process. There are various input parameters which affect PAC, in our experiment we had selected current (I), standoff distance (SOD), pressure (P) and speed (N) as input parameters while, material removal rate (MRR), top kerf width (KT), bottom kerf width (KB), straightness (ST) and bevel angle (θ) had been measured as output responses. Experiments were performed according to L9 array on 6 mm thick SS-304 material and experiment results are listed in Table 1.

Table 1: Experiment Runs

Sl. No.	Input Parameter				Measured Responses				
	Current	Sod	Pressure	Speed	Mrr	Kt	Kb	St	θ
	(I)	mm	Bar	m/min	mm^3/min	mm	mm	mm	Degree
1	30	2.5	4	0.24	3264.77	1.916	1.449	0.191	18.64
2	30	3	4.5	0.32	3869.97	1.829	1.643	0.075	18.57
3	30	3.5	5	0.36	6076.01	1.576	0.905	0.053	12.96
4	35	2.5	4.5	0.43	9162.30	1.751	0.887	0.103	17.71
5	35	3	5	0.20	5279.50	1.57	1.718	0.052	5.72
6	35	3.5	4	0.32	6814.64	2.026	1.694	0.039	9
7	40	2.5	5	0.36	8322.24	1.624	1.334	0.065	7.15
8	40	3	4	0.46	10623.23	2.093	1.297	0.075	7.39
9	40	3.5	4.5	0.24	9328.36	2.089	1.786	0.032	10.39

Artificial Neural Network Model for PAC Process

ANN requires matched pairs of inputs and outputs for the development of suitable network architecture and it is trained to simulate the system to be modeled. The data of PAC input and output experimental results from Table 1 are used for developing ANN model. The central block in Figure 1 is replaced by different architectures of neural networks and an appropriate architecture is determined which limits all the errors within 5%.

The steps listed in the Figure 2 flow chart for the development of neural network models applied in this case as indicated in Table 2. As per the Table 2, beginning from one hidden layered neural network model to three hidden layer model having initially 4 nodes in the hidden layer, the number of nodes in the hidden layer is increased up to 7 while monitoring the error resulting at the end of the training.

The criteria for the termination of training selected are, a) permissible error and b) the maximum number of cycles in training. The limiting value for all the errors over the entire data is selected as 0.05 (5%). The maximum number of training cycles is limited to 1000000 for each learning set. The training stops when any one of the above criteria, namely, all errors being less than 0.05 or 100000 training cycles are completed. The learning rate is kept as 0.6 and momentum as 0.8 for the stable learning and convergence of weights. For training follow the 80–20 rule for neural networks.

With two hidden layers having four nodes in the first hidden layer and six nodes in the second hidden layer and four nodes in input and five nodes in the output layer neural network. Such architecture is denoted by the author as 4–4–6–5 architecture, the numbers denoting first and last numbers for input and output layers respectively, while numbers next to the input layer indicate nodes in the first hidden layer and number of nodes in the second hidden layer respectively.

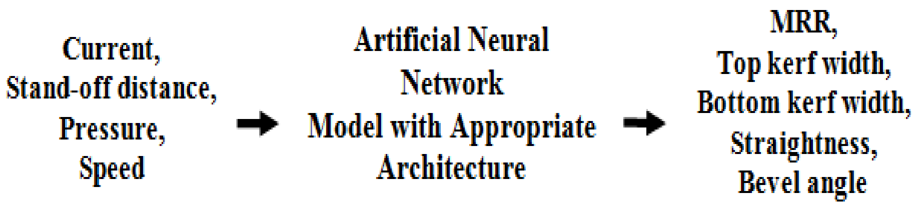

Figure 1: Schematic Artificial Neural Network Model for PAC Process.

Table 2: Neural Network Modeling for PAC Process Modeling

Network Type	Feed Forward
Input for the neural network model	current, stand-off distance, pressure and speed
Number of nodes in input layer = Number of inputs to the neural network model	4
Output from the neural network model	MRR, top kerf width, bottom kerf width, straightness, bevel angle
Number of nodes in output layer = Number of outputs from the neural network model	5
Initial Number of Hidden Layers	1
Maximum Number of Hidden Layers	3
Initial Number of Cells in a Hidden Layer	4
Maximum Number of Cells in a Hidden Layer	7
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

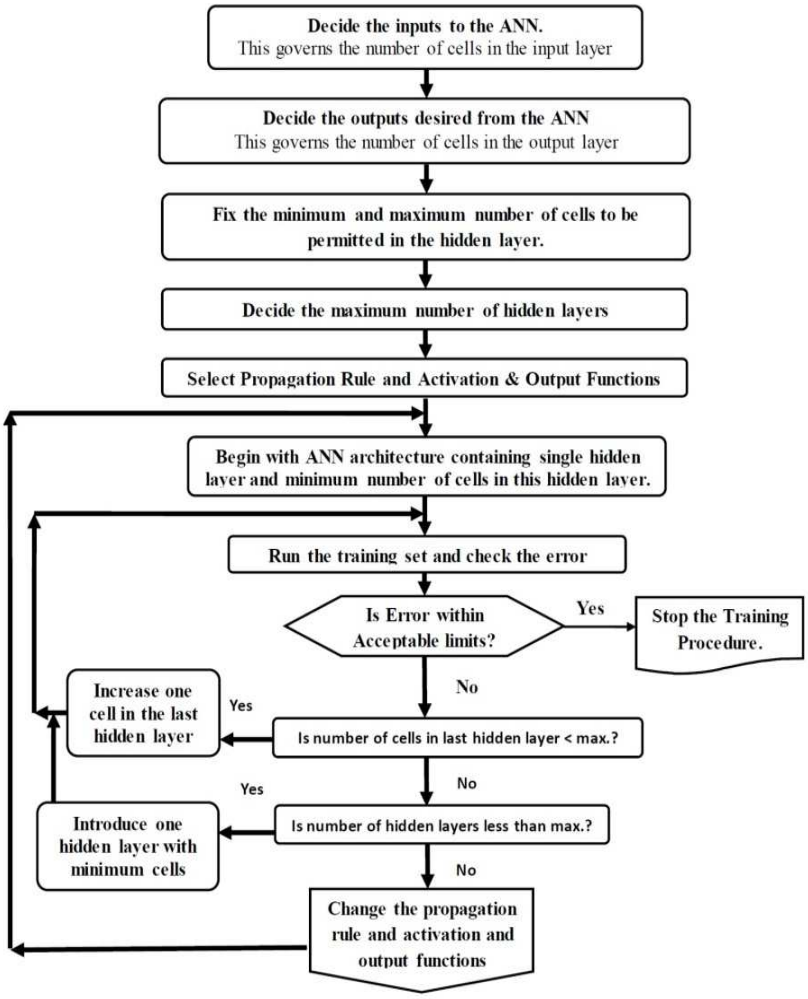

Figure 2: Flow Chart for Neural Network Modeling Approach.

Total 12 different ANN architectures are tried and their results of errors in prediction with their number of learning cycle when training ends with all error value less than the value of 5% permitted as the target error value are shown in Table 3. Listing of the training and test errors can be used for the selection of the most appropriate network architecture. For error calculation equation 1–5 is used.

Error for each case is defined as

$$\text{Error}\% = \frac{|A_e - A_p|}{A_e} \quad (1)$$

$$\text{Error}_{\text{av}}\% = \frac{1}{N}\sum_{i=1}^{N}\frac{|A_{\text{ei}} - A_{\text{pi}}|}{A_{\text{ei}}} \quad (2)$$

where,

Ae = the output value as obtained from theoretical analysis

Ap = The output value predicted by the neural network model

The average error for the entire epoch (complete set of input-output pairs) is defined as

Table 3: Neural Network Architectures & Corresponding Training Results for PAC Process

Sl. No	Model Structure	Avg. Error %	Min. Error %	Max. Error %	Number of Learning Cycles when Training Stopped with all Errors Being Within 5%
1	4–4–5	5.9191	0.3883	22.8125	988
2	4–5–5	5.8453	1.9371	26.5625	615
3	4–6–5	3.7920	0.6667	9.5762	255
4	4–7–5	4.9147	1.0737	14.5794	2367
5	4–4–4–5	9.8083	0.5660	35.1923	473
6	4–4–6–5	8.2935	1.9677	18.2692	231
7	4–5–5–5	7.4872	1.3334	29.6875	306
8	4–6–4–5	7.6269	0.2570	24.3750	1124
9	4–6–5–5	6.6401	1.0667	27.5	205
10	4–4–5–6–5	5.5658	0.7094	26.25	1464
11	4–5–4–6–5	11.6834	1.2	27.8846	947
12	4–5–6–4–5	9.0318	1.0679	29.375	3346

The maximum error is defined as

$$\mathrm{Error}_{\mathrm{max}}\% = \max(\textstyle\sum_{i=1}^{N} \frac{|A_{\mathrm{ei}} - A_{\mathrm{pi}}|}{A_{\mathrm{ei}}} \quad (3)$$

And the minimum error is defined as

$$\% = \min(\textstyle\sum_{i=1}^{N} \frac{|A_{\mathrm{ei}} - A_{\mathrm{pi}}|}{A_{\mathrm{ei}}} \quad (4)$$

For each architecture of neural network model the root mean square value of error is

$$\mathrm{Error}_{\mathrm{rms}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{A^e - A^p}{A^e}\right)^2} \quad (5)$$

For determination of the RMS error the maximum errors out of the three output nodes MRR, KT, KB, ST, θ are used. The value of R (coefficient of determination) and scatter □ can be used to decide upon the best architecture. The R and □ values can be determined as per equation 6 and 7.

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{A^e}{A^p} \quad (6)$$

and, $$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\{R - R_i)^2} \quad (7)$$

As seen from Table 3, the error values are within the limit for some models. In such a situation, it becomes difficult to decide, which architecture is the best representative model of the system. The R and □ test is the most popular approach to handle this situation. The value of errors, R and □ are evaluated using equations 5, 6 and 7 respectively and the training and test errors for all networks are listed in Table 4.

RESULTS AND DISCUSSIONS

It is seen that the value of average and minimum errors are within specified limits for some of the neural network model architectures evaluated and given in Table 3 and Table 4. From these tables, it is observed based on R, □, and RMS error test that model 4-6-5 shows the best performance with R closes to unity being 1.0386 and the value of □ being closest to zero at 0.0365.

Table 4: Training and Test Errors for PAC Process Model

Sl. No	Model Structure	Training Error		Test Error	
		Max. Error%	$Error_{rms}$ %	|1-R|	σ
1	4–4–5	22.8125	8.1655	0.0640	0.0687
2	4–5–5	26.5625	9.5503	0.0596	0.0756
3	4–6–5	9.5762	4.4094	0.0386	0.0365
4	4–7–5	14.5794	6.7122	0.0520	0.0517
5	4–4–4–5	35.1923	14.3081	0.1206	0.1585
6	4–4–6–5	18.2692	10.6366	0.0886	0.0742
7	4–5–5–5	29.6875	11.3221	0.0757	0.0846
8	4–6–4–5	24.3750	10.8802	0.0774	0.0776
9	4–6–5–5	27.5	10.3082	0.0669	0.0786
10	4–4–5–6–5	26.25	9.2514	0.0563	0.0737
11	4–5–4–6–5	27.8846	14.4234	0.1394	0.1188
12	4–5–6–4–5	29.375	12.6410	0.0949	0.0920

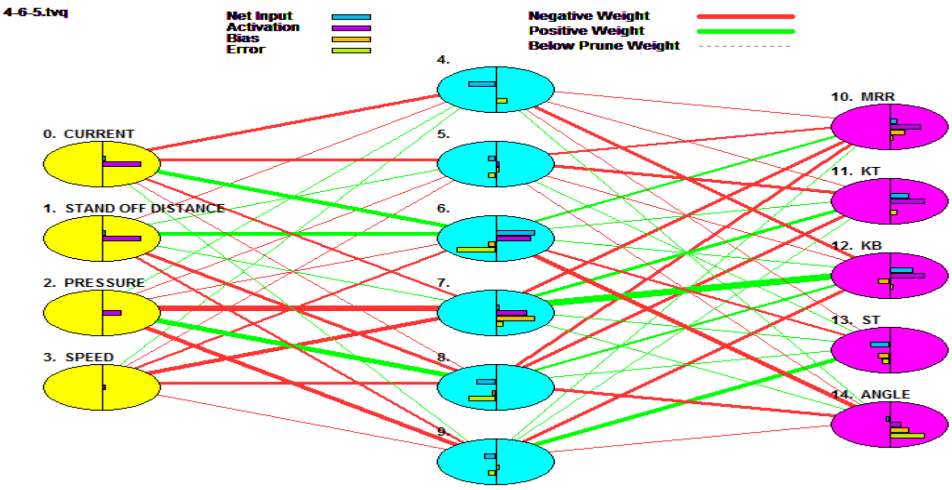

Figure 3: ANN Model of PAC Process with Architecture 4-6-5.

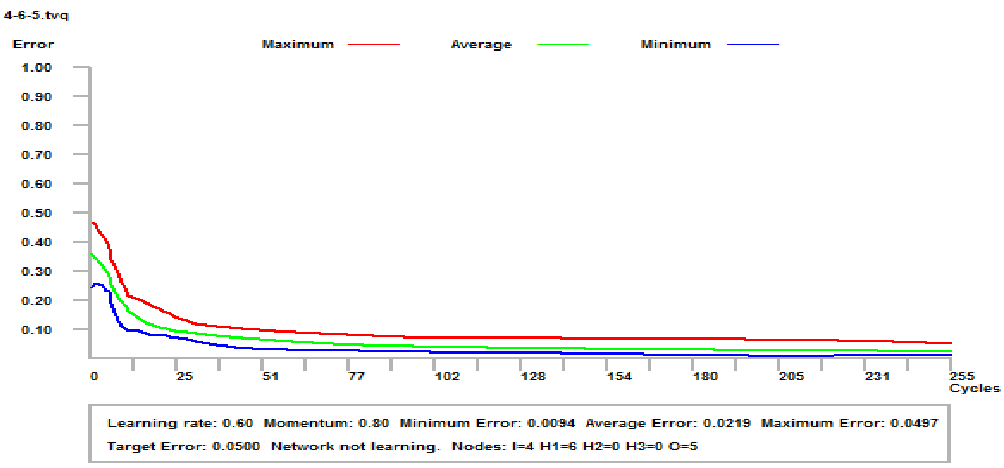

Figure 4: ANN Model Training & Error Propagation Graph with Increasing Number of Training Cycles for the 4-6–5 Architecture.

The RMS error is also the least being 4.4094% and less than 5%. The average error for this model is 3.7920% which is again the least of all other models. Thus it is observed that the model with architecture 4-6-5 is giving better performance than other models tested. Hence model 4-6-5 is selected as the best ANN model among all tested models. The architecture of 4-6-5 and ANN model training and error propagation graph with an increasing number of training cycle of ANN model for PAC process are shown in Figure 3 and Figure 4 respectively.

CONCLUSIONS

The complex relationship between control and response variables for processes like PAC requires model free tools like ANN to capture the relationship accurately. Hence, ANN Model was developed for modeling the relationship between the response and control variables in this work. By evaluating several network architectures, it was found that the 4–6–5 architecture was most suitable on the basis of least errors and value of coefficient of determination being closest to unity.

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AUTHORS PROFILE

Amit H. Patel (Lecturer) is affiliated to the Department of Mechanical Engineering, Polytechnic, The Maharaja Sayajirao University of Baroda, Gujarat, India, since 2013. He completed Master of Engineering program from Faculty of

Technology and Engineering, The Maharaja Sayajirao University of Baroda, Gujarat, India in Production Engineering and undergraduate studies in Mechanical Engineering from A.D.I.T. college, New V.V. Nagar, Gujarat, India.

He has three research publications in international conferences to his credit. His current research interests are in Advanced Machining Processes, Manufacturing Engineering and Industrial engineering. He is Lifetime membership of ISTE.

Dr. Akash B. Pandey (Assistant Professor) is affiliated to the Department of Mechanical Engineering, Faculty of Technology and Engineering, The Maharaja Sayajirao University of Baroda, Gujarat, India, since 2009. He completed Master of Engineering program from Faculty of Technology and Engineering, The Maharaja Sayajirao University of Baroda, Gujarat, India in Production Engineering and undergraduate in Mechanical Engineering from same institute. Also, Earned Doctoral Degree in Mechanical Engineering from Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India.

He has twenty five and more research publications in international Journals/ international conferences, including 10 Keynote lectures/Invited Talks in various institutes to his credit. His current research interests include development of socially useful technological solutions, manufacturing, and control of manufacturing systems. He is Lifetime membership of ISTE.